Code Analysis of Hex Centers for Granular Material

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Granular material is a collection of discrete macroscopic particles characterized by a loss of energy whenever the particles interact with each other. This type of material is characterized as a new form of matter since it behaves so differently under different conditions. Because of this characteristic studying its behavior by using statistical mechanics is very limited, leading us to take different approaches. The main purpose of this research is to study how different variables affect the way granular material behaves by examining the relationship between the angle in which an avalanche is formed to three different variable: the shape of the material, the mix of different shapes, and the locations of those different shapes. This task is performed by analysing large numbers of images taken of the angle of stability of a pile composed of two different shapes, hexagons and dimers. In order to analyse large amounts of data, the automation of the identification of the different shapes present in the images is necessary. To do so, some code was originally developed in IDL but it was later translated to python. Since the translation, the code has not reach satisfactory performance. The way the code works right now is by using a collection of neural networks that identifies the centers of the hexagons. Moreover, after having made some improvements, the code still need some further corrections.

I. INTRODUCTION

Granular material such as sand, snow, rocks, and ball bearing among others are very common in our everyday lives. This type of material is defined as a collection of discrete, macroscopic particles characterized by a loss of energy whenever the particles interact with each other. The study of this material is of great practical importance due to its relevance to many applications such as asteroid impact and the storage of granular material [2]. Moreover, the main reason why we are interested in studying this type of material is because its behavior is very difficult to fully explain or predict by using statistical mechanics since it behaves so differently under different conditions. This material is characterized as a form of matter distinct from solids, liquids, or gases since it does not behave like a single phase of matter but has characteristics of each one depending on the situation. An example that illustrates this characteristic is when we have a pile of sand on an inclined plane. For this example the state of the system depends on the angle of the plane. For instance when the angle of inclination is small the pile of sand will behave like a solid, retaining its shape and structure, and it will not expand to fully fill the available space like a liquid would do. However, when the angle of inclination become steeper (large angle), it will behave like a non-Newtonian fluid, with no constant coefficient of viscosity. The causes of this interesting and dynamic behavior are the inelastic collisions that occur between the particles whenever they interact with each other. Because of the inelastic collisions the energy of the system varies dramatically from moment to moment and the energy cannot be defined. Also, since the particles that make up granular materials are macroscopic the temperature does not matter and therefore the use of statistical mechanics is very limited [3]. Because of limitation, for this project we are approaching this problem by examining the relationship between the angle in which an avalanche is formed to three different variables which are the shape of the material, the mix of different shapes, and the location of those different shapes to gain a better understanding of the behavior of granular materials.

II. EXPERIMENTAL SET-UP

For the experimental set-up used in this research, past students created a two dimensional set-up in which a round rotating drum was filled with 50 % metal ball bearings with the shape of hexagons and the other 50% with ball bearings with the shape of dimers. In this case the green balls are the hexagons and the silver balls are the dimers, as shown in Fig. 1.

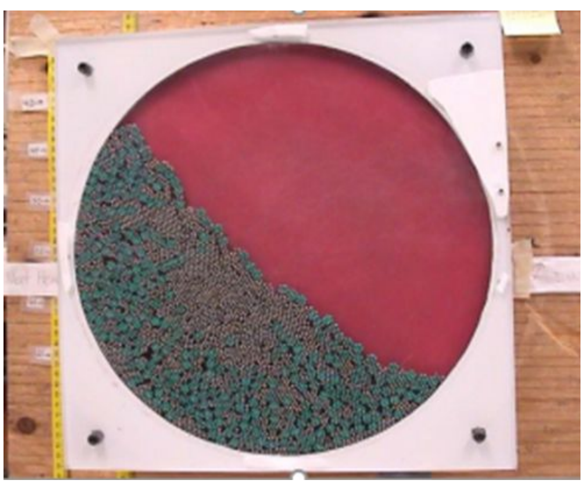


Fig. 1. The experimental setup consists of a rotating drum filled with metal ball-bearings, welded into hexagons (green) and dimers (silver).

For the avalanche simulation this drum was rotated at constant speed by using a motor while a video camera recorded the entire process of the formations of the avalanche along with the exact angle in which it occurred [1]. Furthermore, for this set-up a student wrote some code so that the computer will pick up the beginning of the avalanche instead of having a student scan through the video quickly to look for the frame of the avalanche. The way the set-up works right now is by using a webcam that connects directly to the computer to run the simulations automatically. However the images that were used for this analysis were part of the old images (before the webcam was used).

Moreover, after studying hundreds of avalanches by using histograms of the number of avalanches versus the angle in which they were formed the students were not able to find any pattern relating the avalanche angles to the location of different grains within the pile, since the distribution of avalanches was quite broad within the range of angles. So, they decided that they want it to go beyond hundreds of avalanches to thousands, however this required identifying the exact location of the different shapes present in the image. This needs to be automated in order to analyze large amount of data more efficiently.

III. CODE PORTION OF THE RESEARCH

For the code portion of this project, a program that identifies the location of the different shapes present in an image was developed in IDL and it was later translated to python. In this case what the program identifies are the centers of the hexagons present in images similar to that shown in Fig. 1. In order to look for any trends in the location of the different shapes, it is sufficient to only locate the hex centers, since the avalanches simulations are made up of 50 % hexagons and 50 % dimers.

Now, the way the program works is by using a collection of neural network that trains the program by looking at different color channels.

A neural network learns to perform tasks by considering examples without you programming them, meaning that the information that is sent from the input unit to the output unit is connected by one or more layers of hidden unit which together form the majority of the artificial brain. For the program, the neural networks are trained to recognize a particular shape in an image (in this case a hex center) by giving it a lot of examples of a hex center. The training of the program is composed of five different neural networks; three color neural networks, one position neural network, and a neural network that combines the three color networks. However, during almost the entire summer, we only retrained the program using the three color networks to do the corrections in the code. The reason is that it was faster to run the program using minimum networks and also because the color networks were working better than the other two. All the information for the code errors was obtained using these three neural networks and using the same image from the training for the main program. Our final results were obtained using the five neural networks and also using different images from the training.

Moreover, in order to perform this task the program places limits on where to look for balls by first determining the radius of the drum and both the left and rightmost edge of the pile of balls, as illustrated in Fig. 2. Then, it locates each individual ball by analysing a five by five pixel region to search for the brighter spots in the pixels that are reflected by each ball (Fig. 3).

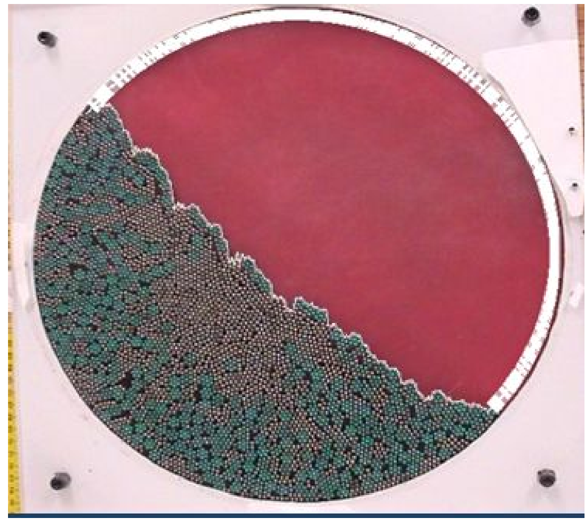


Fig. 2. In this image the program is finding the radius of the drum and the edges of the pile of balls.

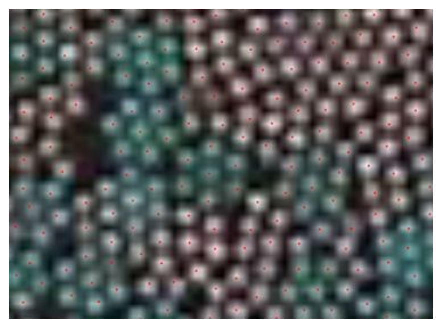


Fig. 3. In this image the program is identifying the brightest spot in the balls and is labeling them as ball centers (red dots).

Once all the balls have been identified as ball centers (based on the brighter spots), the program labels them as either green balls or silver balls. In this case the green balls are the hexagons and the silver balls are the dimers. However, the program only does this for the balls that it is certain to be that color. The balls for which the color is not so clear due to the reflections of other nearby balls and the relatively low resolution of the camera, are labeled as “fuzzy” balls. After all the balls have been identified and labeled in a category, the program then uses the collection of the five neural networks to identify the hex centers. The neural networks use the red, the green, and the blue (RGB) values along with some parameters of the position network to identify the exact location of the hex centers in the images. Now, in order to operate the program we use one image where all the hex centers have been identified manually to train the neural networks (Fig. 4). Then after the training, the computer's solution for how to identify a hex is stored so that it can later be applied to other pictures, when we run the main program. In general, we have two different programs: one to retrain the neural networks and one that identifies the hex centers.

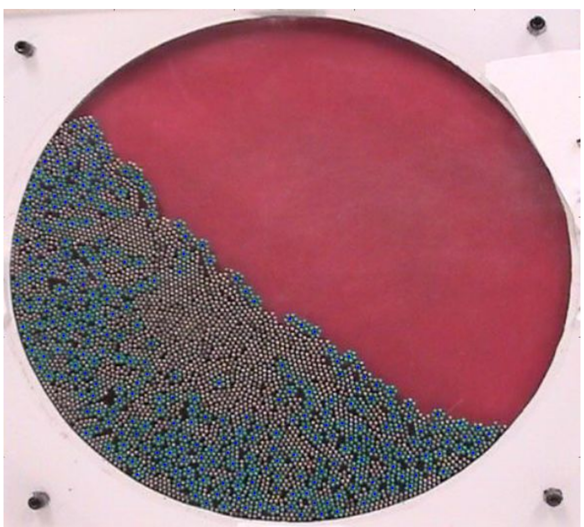


Fig. 4. This image illustrates the correct hex centers (blue balls) that were manually found by a student.

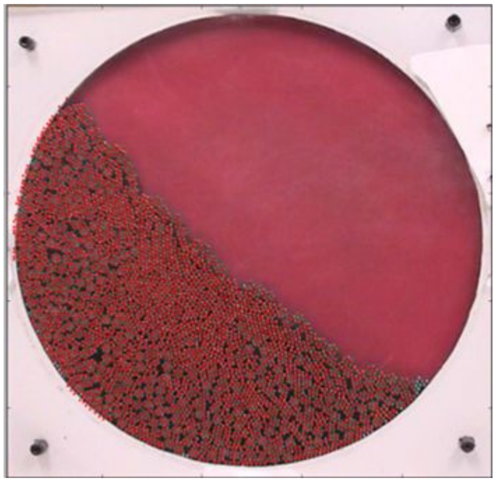
IV. PERFORMANCE

The main focus of this research was to fix the program by correcting some code errors. During the course of the summer, several errors were found and fixed. Many of these errors were related to the algorithm for numbering the balls that the training program and the main program were looking at. This errors were identified by scanning through the code and by comparing the balls found in the images of both programs. In what follows, some of the major improvements made during this summer will be introduced.

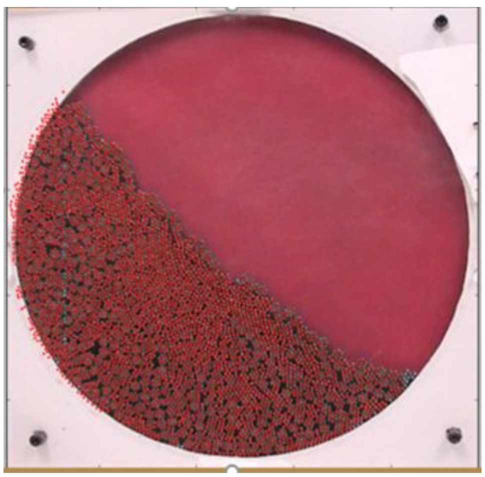
First, one of the primary errors found and fixed was that the balls that the main program and the training were finding were not the same (Fig. 5) since both programs were using different radii at the moment of placing the limits on where to look for balls. Due to this error the training program was finding more non-existent balls outside the drum than the main program as shown in Fig. 5. However after fixing it both programs were finding the same balls and we were able to minimize the non-existent balls outside the drum. Also, an extra fix that was obtained from correcting this error was that we ended up finding some balls inside the drum that the program was ignoring (we still do not know why this occurred). The results after fixing this error are illustrated in Table 1.

	Before Changing the Radius	After Changing the Radius	Actual Total Number of Balls
Main Program	4373	4373	4354
Training Program	4436	4373	4354

Table 1. This table shows the balls that both programs were finding before and after the first correction and the actual number.



Main Program



Training Program

Fig. 5. In this image the red balls represent the balls that both programs are finding.

For the error the numbering for the ball centers was different for the main program and the training, meaning that they were looking at different balls. For example, the training program was identifying one of the balls in the corner as 1 while the main program was identifying that same ball as 3. Due to this error the performance of the programs was poor; however after changing the algorithm we ended up with some major improvements with the identification of the hex centers which are shown in Table 2. In this table the first row states how many hex centers the program found (the percentage is out of the 311 hex centers that the image have) and the second row tells you how accurate the hex centers were compared to the manually hex centers (the percentage is out of the number of hex centers the program identified). This correction also affected the balls that the programs were finding (Table 3.).

311 Hex Centers	Before	After
Hex Centers Correctly Identified	4.20 %	28.43 %
Accuracy of Identified Centers	35.00 %	83.18 %

Table 2. This table represents the results of the hex centers found by the main program using only three neural networks (color networks) for the training.

	Before Changing algorithm	After Changing algorithm	Actual Total Number of Balls
Main Program	4373	4243	4354

Table 3. This table shows the balls that the main program was finding before and after the second correction.

Furthermore, the third error that was fixed during the course of this summer was that some balls inside the drum were getting ignored. This error was occurring because two balls next to each other were getting the same highest pixel of brightness and therefore they were interfering with each other making the program choose only one of them as a ball center while ignoring the other one. For example in Fig. 6, the yellow dot represents the pixel that was getting ignored while the pink dot represents the pixel that it was interfering with the yellow one. This error was fixed by changing the way the program looks for the brighter spots in the balls. Originally the program was selecting the ball centers by using a five by five pixel region and selecting the brightest pixel as the ball center, however this method was problematic since a lot of the balls were getting ignored due to a requirement in which no center could lie within a 5x5 region centered on another center. This was corrected by changing the code of the program, so that now instead of only looking in the five by five area, the program will select the brightest spot in the five by five pixels and then it will exclude the corners so that they do not interfere with the 5x5 region (So now it's ok for two centers to be two pixels apart along a diagonal).

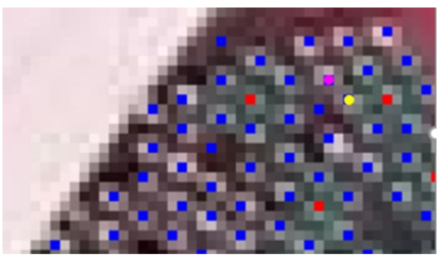


Fig 6. In this image the main program uses a five by five grids region to search for the brighter spots in the pixels. The brightest pixels of each ball (ball centers) are represented by the blue pixels while the red pixels represent the hex centers (also brightest spot). The yellow dot is the ball that the program was ignoring and the pink dot is the ball that was interfering with it.

These changes resulted in significant improvements in performance within the hex centers, as shown in Table 4. However after doing these changes, the program ended up finding a larger total number of balls (Table 5) inside the drum since now it's having a problem with finding non-existent balls inside the drum.

311 Hex Centers	Before	After
Hex Centers Correctly Identified	28.43 %	46.86 %
Accuracy of Identified Centers	83.18 %	96.13 %

Table 4. This table represents the results of the hex centers found by the main program before and after correcting the third error using the three color networks.

	Before Changing 5x5 pixels	After Changing 5x5 pixels	Actual Total Number of Balls
Main Program	4243	4383	4354

Table 5. This table shows the balls that the main program was finding before and after the third correction.

The program need some improvements since it hasn’t reach satisfactory performance yet. There are several errors that still needs to be fixed, however the program ended up with some progress since at the beginning of the summer it was only finding 4.20 % of the hex centers correctly identified (the percentage is out of the 311 hex centers that the image have) and 35 % accurate identified centers (the percentage is out of the number of hex centers that were correct hex centers and the number of hex centers that were mistaken), and now it is finding 81.45 % of the hex centers correctly identified and 97.74 % accurate identified centers (Table 6) using the same image for both the training and the main program. We also obtained good result using a different image from which we did the training (Table 7). This results are the most significant ones since the main purpose of the collection of the neural networks is to train them on one picture and then use them to analyse thousand of other pictures.

311 Hex Centers	Old	Current
Hex Centers Correctly Identified	4.20 %	81.45 %
Accuracy of Identified Centers	35.00 %	97.74 %

Table 6. This table represents the results of the hex centers found by the main program at the beginning of the summer and at the end of the summer using the entire collection of neural networks (five neural networks) for the training.

311 Hex Centers	Current
Hex Centers Correctly Identified	64.95 %
Accuracy of Identified Centers	97.12 %

Table 7. This table represents the results of the hex centers found by the main program at the end of the summer using the entire collection of the neural networks (five neural networks) for the training and using a different image from which we did the training (meaning that the image that it was use for the training was used to analyse a different image for the main program).

Fig. 7 represents the hex centers that the program was finding at the beginning of the summer while Fig. 8 shows the hex centers that the program was finding at the end of the summer using the same image. In this figures we can clearly see the improvements since now the program has fewer random red balls which represents the balls that the program identifies as hex centers and the blue ones represent the correct hex centers that were manually found.

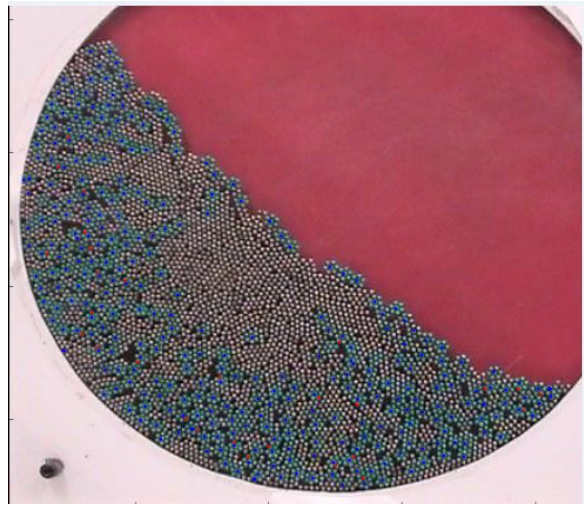


Fig. 7. This image shows the hex centers that were selected manually in blue and the hex centers that the main program was finding at the beginning of the summer in red.

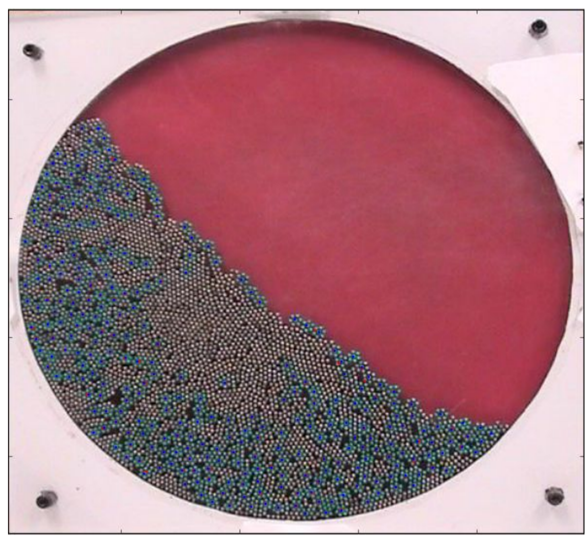


Fig. 8. This image shows the hex centers that were selected manually in blue and the hex centers that the main program was finding at the end of the summer in red (most of the red dots are underneath blue dots meaning that they were overlapping with the correct hex centers).

The balls (Table 8) also had some improvements since now the program is finding less balls outside the drum, however we're now having a problem with non-existent balls inside the drum that needs to be fixed.

	Old Balls	Current Balls	Actual Balls
Main Program	4373	4383	4354
Training Program	4436	4383	4354

Table 8. This table represents the results of the balls found by the main program and training program at the beginning of the summer and at the end of the summer.

V. CONCLUSION AND FUTURE WORK

In the course of this summer, real progress was made within the code, but it still needs some further corrections before it can be used to fulfill its purpose. For now, the program is working at a really good level with finding the hex centers compared to what it was doing before several corrections were made. However the program still needs to be more accurate before we can use it to analyze the variables studied. Some of the sections in which the program still needs some further work are at making a better job in identifying the total number of balls in the drum and their positions.

There are still several errors that we were unable to fix such as fixing the problem with the non-existent balls that the program finds outside and inside the drum, improving the fine adjustment that identifies the center to better than one pixel, and lastly getting good numbers for the ball centers. The later issue seems to be the main limitation in training the neural networks (that's why the position network has so much trouble compared to the others).

Regardless of all the corrections that still needs to be made we ended up with good results since now the program is finding more than 200 hex centers out of the 311 existing hex centers, which means that indeed the position of the balls was the greatest problem fixed with the program. Currently, the networks can be retrained and in that process the program successfully produces similar results to the old neural network.

Compared to 2009, it appears that the code ended up almost ready to reach its peak level of accuracy. Once the networks reaches that point, the program could then be used to analyze large amounts of data for the avalanche simulations in a short time and therefore examine the effect of the three different variables studied (shape of the material, the mix of different shapes, and the location of those different shapes) within the angle of stability of an avalanche of a granular material.

ACKNOWLEDGMENT

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